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The effects of nutritional labels on obesity

Maria L. Loureiro[a,*], Steven T. Yen[b], Rodolfo M. Nayga, Jr[c,d]

[a]Departamento de Fundamentos da Análise Económica, Universidade de Santiago de Compostela, Santiago de Compostela, 15782, A Coruña, Spain
[b]Department of Agricultural and Resource Economics, The University of Tennessee, Knoxville, TN 37996-4518, USA
[c]Department of Agricultural Economics and Agribusiness, University of Arkansas, Fayetteville, AR 72701, USA
[d]Norwegian Agricultural Economics Research Institute, Oslo, Norway

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Abstract

This study examines the relationship between nutritional label use and obesity using switching regression. Results for treatment effect show that nutritional labels play a role in reducing obesity among users of nutritional labels, notably among women. The average body mass index (BMI) for men who read nutritional labels is 0.12 point lower than men who do not read them, while women who are users of nutritional labels have 1.49 points lower BMI than women who do not read labels. These findings imply that health education campaigns can employ nutritional labels as one of the instruments for reducing obesity.

JEL classification: I12

Keywords: Copula; Nutritional labels; Obesity; Overweight; Switching regression

1. Introduction

Obesity is one of the most important health problems currently confronting Americans. The number of adults who are overweight or obese has continued to increase over time. In 2009, 26.7% of the adult population in the United States (U.S.) were obese with the highest prevalence seen among non-Hispanic blacks (36.8%), Hispanics (30.7%), and the elderly aged 50–59 years (31.1%) and 60–69 years (30.9%) (U.S. CDC, 2010).

As the prevalence of overweight and obesity has increased in the U.S., so have related healthcare costs, both direct and indirect. A recent study estimated annual medical spending due to overweight and obesity to be as much as $92.6 billion in 2002 dollars, which amounted to 9.1% of U.S. health expenditures (Finkelstein et al., 2005). Obesity is a result of energy imbalance over a long period of time. This involves eating too many calories and not getting enough physical activity. Most published economic research provided an explanation for the increased growth of obesity rates by analyzing factors that may contribute to this imbalance of caloric consumption and usage (see Chou et al., 2004; Cutler et al., 2003; Lakdawalla and Philipson, 2002; Loureiro and Nayga, 2005; Philipson and Posner, 1999).

In addition to these factors related to supply and demand shifters, Miljkovic and Nganje (2008) utilized the theory of myopic addictive behavior in food consumption and found that lower current and past real prices of sugar contribute significantly to higher values of body mass index (BMI), and increase the likelihood of becoming obese in the U.S. Miljkovic et al. (2008) further appealed to the theory of rational addiction and found that additional taxes on future prices of the addictive (sweet) foods decrease current sugar consumption and BMI.

Concerns about the obesity issue and the effect of diet on health have partly resulted in the legislation of the Nutrition Labeling and Education Act (NLEA) in 1990. The NLEA regulations require the display of a "Nutritional Facts" panel on processed foods. The panel first provides information about the standard serving size; calories are then listed, followed by a breakdown of the constituent elements. Elements such as total and saturated fats, cholesterol, and sodium must always be shown, and other nutrients can be suppressed if they are zero. The regulations also update the list of nutrients that appear on the nutritional facts panel, standardize serving sizes, and define nutrient content claims and health claims. In July 2011, the European Union (EU) proposed a change in its food labeling regulation and mandated that the energy content and amounts

*Corresponding author. Tel.: 34-881811674; fax: 34-981547134. *E-mail address*: maria.loureiro@usc.es (M. L. Loureiro)

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of fat, saturated fats, carbohydrates, sugars, protein, and salt all be stated in a legible tabular form on the packaging and expressed on a per 100 g or per 100 ml basis (Food Law News, 2011). Thus, the 1990 NLEA passed in the U.S. has set a strong precedence for the most recently approved modifications of the EU Nutritional Labeling Directive. Also, due to the mounting importance of food away from home, a new law in the U.S. is now requiring restaurants and similar retail food establishments with 20 or more locations to list calorie content information for standard items on restaurant menus and menu boards (U.S. FDA, 2011).

Zarkin et al. (1993) estimated that the potential health benefits from better diet due to the nutritional labels could be as much as 1.2 million life years gained in the U.S. during the next 20 years. The U.S. Department of Agriculture (USDA) also estimated that improved diets could save $48 billion in annual medical costs and lost productivity resulting from disability, and another $28 billion annually in the value of premature deaths (Frazao, 1999). These estimates, however, are contingent upon the presumption that consumers' food intakes are improved by nutritional label use.

Our interest in this research is the extent to which nutritional labels, as mandated by the NLEA, help Americans manage the risk of obesity. The purpose of this article is to conduct an empirical analysis of the possible relationship between nutritional label use and individuals' body weight as represented by the BMI. Using data from the National Health Interview Survey (NHIS), we employ a copula approach to the switching regression model (SRM) that allows estimation of BMI equations by label-use category, the determination of which is subject to endogenous sample selection. The SRM allows answering of three questions: (1) who uses nutritional labels? (2) what determines BMI? and (3) to what extent might nutritional label use help reduce obesity?

Nutritional label use has been extensively investigated by many authors (Drichoutis et al., 2005; Lewis et al., 2009; Post et al., 2010 among others). Previous research generally concluded that nutritional labeling is most used by informed individuals (Drichoutis et al., 2005), those with some chronic conditions (Post et al., 2010), and those who are overweight or obese (Lewis et al., 2009; Loureiro et al., 2006).

With respect to the link between labeling and nutrition, Kim et al. (2000) found that nutritional labeling decreases individuals' average daily intakes of calories from total fat and saturated fat, cholesterol, and sodium. More recently, and in terms of their impact on obesity, Variyam and Cawley (2006) showed that nutritional labeling policies do not affect obesity levels in the U.S. overall, although they had a positive impact for certain groups, in particular, non-Hispanic white females. As a result of the new labels introduced by the NLEA, the BMI and probability of obesity among white female label users were significantly lower than they would have been in the absence of these informational devices.

Evaluating the impacts of nutritional policies is rather complex and research at times provides contradictory findings. For example, Variyam (2008) found that nutritional labels increase fiber and iron intakes of label users compared with nonusers. Drichoutis et al. (2009), on the other hand, using propensity score matching method and the 2005–2006 National Health and Nutrition Examination Survey (NHANES), showed that in general the NLEA labeling does not have any impact on BMI. In sum, previous studies differ in analytical approaches, data, and findings. Thus, at this point, further analyses are needed. Our current SRM estimates generally suggest that nutritional label use reduces obesity. This finding is robust across gender but the effects are more pronounced among women.

2. Empirical model: a copula approach to the SRM

Our main hypothesis is that individuals select nonrandomly into two separate states: use (reading) and nonuse of nutritional labels, and that BMIs are determined by economic, sociodemographic, and lifestyle variables in two distinctive fashions depending on the label-use outcomes. We are interested in testing hypotheses about self-selection of individuals into label uses, and identifying factors that determine nutritional label use and BMIs. We are also interested in assessing the effect of label use on BMI outcome. All these call for estimation of some form of self-selection model, and we choose the SRM. SRMs have had a long history in economics, dating back to Roy (1951) who was concerned with an individual's decision between earning income as a fisherman and a hunter. See Vijverberg (1993) for a review of its applications in labor economics and other areas of economics. The SRM is best explained by introducing three latent equations: for label use (Y_1^*), BMI outcomes for label users (Y_2^*), and BMI outcomes for nonusers (Y_3^*):

$$Y_1^* = x_1'\beta_1 + u_1, \tag{1}$$

$$Y_2^* = x_2'\beta_2 + u_2, \tag{2}$$

$$Y_3^* = x_3'\beta_3 + u_3, \tag{3}$$

where, for $j = 1, 2, 3$, x_j are vectors of explanatory (economic, sociodemographic, and lifestyle) variables, β_j are conformable parameter vectors, and u_j are random error terms (observation subscripts suppressed). The outcome for label reading (L) is governed by a binary process such that

$$\begin{aligned} L &= 1 \quad \text{if } Y_1^* > 0 \\ &= 0 \quad \text{if } Y_1^* \leq 0. \end{aligned} \tag{4}$$

The two alternative states (sample regimes) for BMI outcomes are determined by the switching (sample selection) mechanism

$$\begin{aligned} y &= Y_2^* \quad \text{if } Y_1^* > 0 \text{ (or if } L = 1) \\ &= Y_3^* \quad \text{if } Y_1^* \leq 0 \text{ (or if } L = 0). \end{aligned} \tag{5}$$

The sample observations (L, y) are $L = 1$ and $y = Y_2^*$ for a label user ($Y_1^* > 0$) and $L = 0$ and $y = Y_3^*$ for a nonuser ($Y_1^* \leq 0$).

Consider univariate cumulative (marginal) distribution functions (cdf's) $F_i(y_i^*) = \Pr(Y_i^* \leq y_i^*)$, probability density functions (pdf's) $f_i(y_i^*)$, and bivariate cdf's $F_{ij}(y_i^*, y_j^*) = \Pr(Y_i^* \leq y_i^*, Y_j^* \leq y_j^*)$ and pdf's $f_{ij}(y_i^*, y_j^*)$ for $i, j = 1,2,3$ and $i \neq j$. The observation rule (5) implies the following sample likelihood function (Amemiya, 1985; Smith, 2003, 2005)

$$\begin{aligned} L &= \prod_{L=0} \int_{-\infty}^{0} f_{13}(y_1^*, y_3)\, dy_1^* \prod_{L=1} \int_{0}^{\infty} f_{12}(y_1^*, y_2)\, dy_1^* \\ &= \prod_{L=0} \frac{\partial}{\partial y_3} F_{13}(0,\ y_3) \prod_{L=1} \left\{ f_2 - \frac{\partial}{\partial y_2} F_{12}(0,\ y_2) \right\}. \end{aligned} \tag{6}$$

The likelihood function in (6) can be expressed either by partially integrating the bivariate pdf's or partially differentiating the bivariate cdf's. The copula approach begins with specifications of bivariate copulas (which are cdf's) so the second line of (6) proves to be the most useful.

Empirical applications of SRMs have been based predominantly on the bivariate normal distributions of the random error terms (u_1, u_2) and (u_1, u_3) [and therefore of the latent dependent variables (Y_1^*, Y_2^*) and (Y_1^*, Y_3^*)].[1] With the bivariate normal distributions, the model characterized by (4) and (5), with likelihood function (6), corresponds to the (conventional) Gaussian SRM. Maximum-likelihood estimation of the Gaussian SRM is discussed by Amemiya (1985, pp. 399–400), who names the model type 5 tobit, and by Maddala (1983, p. 223); the latter also covers a two-step estimation procedure. An important shortcoming of the Gaussian SRM, and any other Gaussian selection models, is that empirical estimates are inconsistent if the assumption of bivariate normal distribution is violated. The literature has focused on development of semiparametric and nonparametric versions of these models to overcome restrictiveness of the Gaussian selection models (Härdle and Manski, 1993). We follow the approach of Smith (2003, 2005) to stay parametric, by replacing the bivariate normal distributions of the random variables with copulas to construct an SRM that is free from the straightjacket of the bivariate normal distributions, although the marginal distributions remain normal as a result of comparison with nonnormal alternatives. The copula SRM approach is superior to the conventional approach in that skewness in the error terms (u_1, u_2, u_3), and therefore of the random variables (Y_1^*, Y_2^*, Y_3^*), is allowed while accommodating their correlations. Our empirical specification is complete by parameterizing the cdf's F_{12} and F_{13} as the Frank copulas (Smith, 2003, 2005) with Gaussian margins. Further development of the likelihood function (6) into the copula case and details on our empirical approach are presented in the Appendix. Besides the continuous sample selection model (Smith, 2003) and SRM (Smith, 2005), the copula approach has also been applied to a variety of other models such as count-data models (Cameron et al., 2004), ordered probability models with endogenous treatment (Yen et al., 2010) and switching (Yen et al., 2012), and censored equation systems (Yen and Lin, 2008).

Given the BMI regression functions specified in (2) and (3) and upon obtaining maximum-likelihood estimates $\hat{\beta}_2$ and $\hat{\beta}_3$ for their parameters β_2 and β_3, the average treatment effect (ATE) of label use is calculated as follows for a sample of T observations (Heckman et al., 2003; Smith, 2005, p. S55):

$$\widehat{\text{ATE}} = \frac{1}{T} \sum_{t=1}^{T} (\hat{\beta}_2 x_{2t} - \hat{\beta}_3 x_{3t}). \tag{7}$$

This ATE measures the expected change in the dependent variable (BMI) resulting from the treatment (label use). For statistical inference, the standard error of the ATE is calculated with the delta method (Spanos, 1999).

3. Data

Data from the 1998 NHIS are used. Collected by the National Center for Health Statistics (NCHS) of the U.S. Centers for Disease Control and Prevention (U.S. CDC-NCHS, 1998), the NHIS data are widely used to monitor trends in illness and to analyze public health issues. While the NHIS has been conducted continuously since 1957, only a few cross sections offer supplementary information about nutritional label use, the latest being the 1998 cross section employed in this study. The NHIS data also contain information on other health indicators, health-/diet-related knowledge, socioeconomic background, and residence location of each individual. BMI is a primary measure of obesity and is calculated as weight in kilograms divided by height in meters squared. After excluding outlier observations in the BMI variable, a sample of 25,640 observations (10,810 men and 14,830 women) is used in the analysis. The definitions and sample statistics of variables are exhibited in Table 1. The endogenous variables are BMI and a binary indicator for nutritional label use, recoded such that always/often/sometimes = 1 and rarely/never = 0. Variyam (2008) used the same coding.

Explanatory variables include personal and household characteristics, demographic, geographic, and socioeconomic characteristics, as well as proxies for a set of attitudinal/physiological factors that pre-dispose respondents to read nutritional labels. Personal and household characteristics include age, education, race, home ownership (home, apartment, trailer), income, and education.[2] Other demographic factors include region, rural or urban community, household size, and seasonal dummies which capture variations in preferences and other outside factors (such as temperature variation) across the country. This general specification was also used by Kim et al.

[1] The two sample regimes for label users and nonusers are mutually exclusive and therefore the error correlation ρ_{23} between the two regime regression equations is not estimable. The trivariate distribution of (u_1, u_2, u_3) therefore amounts to two separate bivariate distributions.

[2] Home ownership reflects household wealth, and residing in an apartment or trailer reflects lifestyle.

Table 1
Variable definitions and sample means

Variable	Definition	Men	Women
Endogenous variables			
Label use	Reading nutritional labels: 0 = never, never seen or rarely; 1 = sometimes, often or always	0.58	0.74
BMI	Body mass index: weight in kilograms divided by height in meters squared (kg/m^2) total sample	26.32 (4.51)	25.53 (5.70)
	Body mass index: label users	26.58 (4.54)	25.59 (5.69)
	Body mass index: label nonusers	25.97 (4.44)	25.36 (5.73)
Continuous explanatory variables			
Family size	Number of members in household	2.37 (1.42)	2.58 (1.48)
CPI food	Consumer price index of food	161.22 (4.40)	161.20 (4.35)
Binary explanatory variables (yes = 1, no = 0)			
Kids	Children under 18 are present in the household	0.38	0.39
Quarter 1	Interviewed during first quarter of the year (reference)	0.28	0.22
Quarter 2	Interviewed during second quarter of the year	0.26	0.26
Quarter 3	Interviewed during third quarter of the year	0.26	0.26
Quarter 4	Interviewed during fourth quarter of the year	0.25	0.26
Black	Race is black	0.11	0.14
Other	Race is other nonwhite	0.07	0.07
White	Race is white (reference)	0.82	0.79
Low income	Household income <\$20,000	0.22	0.22
High income	Household income above \$50,000	0.39	0.39
Med. income	Household income >\$20,000 and <\$50,000 (reference)	0.39	0.39
Married	Individual is married	0.53	0.48
Widowed	Individual is widowed	0.04	0.13
Divorced	Individual is divorced	0.14	0.17
Partner	Individual is cohabitating with a partner	0.05	0.04
Single	Individual or single (never married) (reference)	0.24	0.18
Northeast	Resides in the Northeast	0.18	0.20
Midwest	Resides in the Midwest	0.25	0.24
South	Resides in the South	0.34	0.35
West	Resides in the West (reference)	0.23	0.21
Rural	Resides in a rural (nonmetropolitan) area	0.29	0.28
Urban	Resides in the central city	0.49	0.49
Suburb	Resides in a suburban area (reference)	0.22	0.23
Apartment	Owns an apartment	0.28	0.29
Home	Owns a home (reference)	0.66	0.65
Trailer	Owns a trailer	0.06	0.06
Basic education	Completed primary levels	0.15	0.17
High school	High school (reference)	0.39	0.40
Some college	Some college	0.29	0.29
Bachelor	Obtained a Bachelor's degree	0.17	0.14
Graduate	Obtained post-graduate education	0.09	0.07
Age 18–25	$18 \leq$ age ≤ 25	0.12	0.12
Age 26–40	$26 \leq$ age ≤ 40 (reference)	0.35	0.33
Age 41–65	$41 \leq$ age ≤ 65	0.39	0.38
Age ≥ 66	Age ≥ 66	0.14	0.17
Smoker	Currently smoking cigarettes	0.26	0.22
Walk exercise	Walk for exercise	0.44	0.53
Outdoors	Working outdoors	0.09	0.01
Sample size		10,810	14,830

Note: Standard deviations in parentheses.

(2000) and Drichoutis et al. (2009) in the label-use modeling literature and by Chou et al. (2004) in modeling obesity incidence. Note that even though the copula approach is very flexible and the system is fully identified without exclusion restrictions, we estimate our model with exclusion restrictions to further facilitate identification; hence the different sets of explanatory variables in the selection (label use) and BMI regression equations. Such restrictions are based on previous economic literature on the topic.

The sample average BMIs are 26.32 for males and 25.53 for females. BMI levels decrease to 25.97 and 25.36 for label users. About 58% of the sample are overweight and close to 24% are obese; these statistics are comparable to those found in other data sets like NHANES (U.S. CDC, no date).

The frequency distribution of label use by gender suggests that females have a higher propensity to use nutritional labels, with 74% of women indicating use of nutritional labels, compared to only 58% of males. Table 1 also shows the sample statistics of the control variables used, for males and females.

4. Results

Baseline ordinary least squares (OLS) regressions are run to explore the relationship between label use and BMI by gender (results available upon request). Main results suggest that both education and age decrease BMI labels, whereas family size has a positive impact on BMI. However, label use increases BMI. This counterintuitive result suggests a closer look at the multivariate relationship, especially the potential endogeneity of the label-use variable. The model, Frank's copula with Gaussian margins (henceforth, Frank–Gaussian model), is estimated by programming the likelihood function (Eq. 6, which simplifies to Eq. A.4) in GAUSS.[3] The label use (switching) and BMI regressions are modeled as a function of common explanatory variables denoting the economic and sociodemographic characteristics of participants. A set of restrictions are used to identify the model parameters. Specifically, the consumer price index (CPI) for food and a variable denoting whether the individual works outdoors are included in the BMI equation but not in the switching equation. The literature suggests that these two variables (or closely related ones) are determinants of BMI levels (Chou et al., 2004; Cutler et al., 2003; Loureiro and Nayga, 2005), and that there is no *a priori* expectation that they may affect the propensity to read nutritional labels during food shopping.

[3] Model selection is done with Vuong's (1989) nontested test. In particular, we compare the likelihood of the Frank–Gaussian model with that of the Gaussian–Gaussian model. The latter has lower likelihoods for both genders which was also rejected by Vuong's tests, with standard normal statistics $z = 14.11$ for males and $z = 19.61$ for females. In addition, we also estimated the Clayton–Gaussian and Gumbel–Gaussian models, both of which were rejected by the data, due to the restricted parameter space (positive error correlation) of these copulas (Nelsen, 2006; Smith, 2003). In sum, among the various alternatives, our data favor the use of the Frank–Gaussian model.

The roles of gender and appropriateness of pooling the samples are investigated by an likelihood ratio (LR) test. Results show that coefficients vary by gender, with the null hypothesis of equal parameters rejected ($LR = 890.97$, $df = 95$, P-value < 0.0001). Thus, the model is estimated separately for males and females (pooled sample results are available upon request). The parameter estimates are presented in Table 2. For both men and women, we find evidence of a negative association between the latent variables for label use and BMI for label users, as reflected by negative and significant estimate for the concordance parameter ($\hat{\theta}$) and Kendall's τ ($\hat{\tau}_{21}$), but a positive association between the latent variables for label use and BMI for nonusers ($\hat{\lambda}$, $\hat{\tau}_{31}$). These correlation estimates can be interpreted as a negative effect of nutritional label use on BMI. On statistical grounds, significance of these correlations also provides evidence of nonrandom selection of sample individuals into user and nonuser groups and justifies use of the endogenous SRM, vis-à-vis an exogenous switching model. In this latter case, the regime BMI equations can be estimated separately with segmented (user and nonuser) samples.

We first describe estimation results for the label-use equation. For males, positive and significant determinants of nutritional label use include having higher education levels (college, bachelor, and graduate), and being older (age $\geq$25), in addition to high income, urban location, race (black), being married, walking for exercise, and the Northeast variable. Negative factors of nutritional labeling use include household size, being of another race (than white and black), being between 18 and 25 years of age, being a smoker, and having basic education.

The label-use equation estimates suggest many similar factors affecting nutritional label use in both males and females. Specifically, variables contributing positively to nutritional label use for females are educational attainment (above primary school), age ($\geq$25), living in an urban location, walking for exercise, being married, and residing in the Northeast, Midwest, or South area of the U.S. Variables with a negative effect on label use are household size, being of another race (than white or black), being widowed, having basic education, being a smoker, being of a younger age (18–25), living in a trailer, or in an apartment. As in males, age exhibits a nonlinear relationship with label use. Previous studies also showed that nutritional labeling use increases with education and income (Drichoutis et al., 2005; Kim et al., 2000), but decreases for male and with household size (Kim et al., 2000).

Also presented in Table 2 are the regime regression estimates for the BMI equations for label users and nonusers and by gender. Among men who read labels, BMIs tend to be higher for those who live in larger households, are black, live in a trailer, want to lose weight, are between 41 and 65 years old, have basic education, work outdoors, and live in the South. The negative effects of education on BMI are consistent with the OLS estimates reported by Chou et al. (2004) based on data from the 1984–1999 Behavioral Risk Factor Surveillance System (BRFSS). Another variable with a negative effect on BMI is whether the individual walks for exercise. Physical activity has been found to play a key role in BMI (Cutler et al., 2003; USDHHS, 1996) and this negative effect of walking reflects the role of physical activity. Corroborating findings reported in the literature (Chen et al., 2005; Chou et al., 2004), blacks have higher BMIs than whites on average, among both nutritional label users and nonusers.

The effects of variables on BMI among female label users are similar to those among male users. Variables that have a positive effect on BMI are household size, living in an apartment or a trailer, being black, having basic education, and being between 41 and 65 years of age. On the other hand, variables that affect BMI in a negative and statistically significant way are the educational variables corresponding with some college, a bachelor's degree, graduate education, being married or having a partner, living in an urban area, being a smoker, walking for exercise, and being between 18 and 25 years of age. As expected, walking decreases BMI for both males and females.

ATEs are calculated to quantify the impact of reading nutritional labels on obesity (see Eq. 7). The results, presented in Table 3 by gender and race, suggest that the use of nutritional labels generally reduces BMI. The average BMI for men who read nutritional labels is 0.12 point lower than those who never/rarely read them. Compared to men, nutritional labeling has a more notable effect on women who are more frequent users of nutritional labels. Women who read labels have 1.49 points lower BMI than women who do not read labels. Considering that an average man in the U.S. is 1.76 cm (5′ 93″) tall and weighs 86 kg (190 lbs.), a reduction of 0.12 point in BMI implies a loss of 0.37 kg (0.82 lb). For an average woman, at 162 cm (5′ 38″) and 74 kg (163 lbs.), a reduction of 1.49 points in BMI corresponds with a weight loss of 3.91 kg (8.6 lb). These magnitudes are encouraging with respect to the impact of nutritional labeling on weight outcomes. The fact that labels have a smaller BMI effect on men than on women may be related to the fact that the basal metabolic rates (daily caloric needs) of men are higher than those of women, so that a reduction of 100 calories in food intake, for instance, has a greater impact on weight for females than males.

The ATEs also differ by race and gender. White men who read labels have a 0.25 lower BMI than white men who do not read labels. This racial difference is also found in women. Although label-reading women of the white, black, and other races have lower BMIs than their counterparts who do not read labels, there is a considerable gap in the effect of labels on BMI reduction for females across races. The highest BMI reduction is seen in white females who read labels. These females have a BMI that is 1.76 points lower than that of white females not reading labels. In contrast, the smallest reduction in BMI is found for women of other races who read labels, with a statistically insignificant effect. In sum, there are clear gender and race differences in the effects of nutritional labels on body weight. These mean effects reflect the majority in the sample; 82% of the male sample and 79% of the female sample are whites.

Our findings are more promising than those reported by Variyam and Cawley (2006), who showed that implementation

Table 2
Maximum-likelihood estimates of switching regression model: Frank's copula with Gaussian margins

Variable	Men: Switching: Label use	Men: BMI (Label = 1)	Men: BMI (Label = 0)	Women: Switching: Label use	Women: BMI (Label = 1)	Women: BMI (Label = 0)
Constant	−0.184***	19.660**	30.325***	0.212***	43.314***	31.632**
	(0.068)	(8.008)	(9.196)	(0.069)	(7.621)	(13.457)
Family size	−0.029**	0.186***	0.116**	−0.036***	0.337***	0.112*
	(0.012)	(0.055)	(0.058)	(0.010)	(0.044)	(0.067)
Kids	0.006	−0.006	−0.047	0.006	−0.001	0.171
	(0.026)	(0.122)	(0.137)	(0.024)	(0.114)	(0.183)
Quarter 2	0.047	−0.354*	0.211	−0.017	0.098	−0.089
	(0.036)	(0.184)	(0.209)	(0.034)	(0.174)	(0.277)
Quarter 3	0.005	−0.201	0.318*	−0.060*	0.036	−0.048
	(0.037)	(0.173)	(0.195)	(0.034)	(0.164)	(0.261)
Quarter 4	0.026	−0.295	0.224	−0.024	0.141	0.159
	(0.037)	(0.196)	(0.217)	(0.034)	(0.182)	(0.295)
Black	0.078*	0.918***	0.352*	−0.023	2.372***	1.411***
	(0.042)	(0.182)	(0.212)	(0.035)	(0.160)	(0.252)
Other	−0.106**	−0.319	−0.639**	−0.140***	0.449*	−0.746**
	(0.051)	(0.234)	(0.255)	(0.046)	(0.237)	(0.332)
Low income	−0.002	−0.063	0.081	0.016	0.240*	0.080
	(0.034)	(0.158)	(0.179)	(0.031)	(0.145)	(0.231)
High income	0.065**	−0.223*	−0.114	0.019	−0.022	−0.047
	(0.029)	(0.134)	(0.149)	(0.027)	(0.126)	(0.202)
Married	0.076*	0.128	0.578***	0.115***	−0.890***	0.013
	(0.041)	(0.184)	(0.212)	(0.038)	(0.173)	(0.273)
Widowed	−0.027	−0.397	0.240	−0.121**	−0.112	−0.340
	(0.077)	(0.374)	(0.415)	(0.052)	(0.255)	(0.394)
Divorced	−0.052	0.094	0.097	0.002	0.087	−0.147
	(0.046)	(0.212)	(0.244)	(0.042)	(0.187)	(0.304)
Partner	0.101	−0.252	0.372	−0.050	−0.512	−0.398
	(0.065)	(0.306)	(0.329)	(0.065)	(0.331)	(0.452)
Northeast	0.181***	0.049	0.494	0.214***	−0.568**	0.022
	(0.041)	(0.283)	(0.319)	(0.037)	(0.265)	(0.446)
Midwest	0.015	0.706	0.136	0.230***	−0.730	0.802
	(0.038)	(0.493)	(0.561)	(0.035)	(0.471)	(0.828)
South	0.048	0.878*	0.254	0.185***	−1.163**	0.265
	(0.036)	(0.518)	(0.593)	(0.033)	(0.493)	(0.860)
Rural	−0.057	0.056	−0.247	−0.014	0.019	−0.025
	(0.036)	(0.170)	(0.183)	(0.033)	(0.155)	(0.248)
Urban	0.085***	−0.282*	−0.099	0.064**	−0.425***	−0.106
	(0.033)	(0.154)	(0.172)	(0.030)	(0.142)	(0.229)
Apartment	0.021	−0.155	−0.190	−0.081***	0.300**	0.325
	(0.033)	(0.153)	(0.169)	(0.029)	(0.138)	(0.214)
Trailer	−0.005	0.782***	0.468*	−0.086*	1.366***	0.511
	(0.054)	(0.246)	(0.245)	(0.048)	(0.235)	(0.326)
Age 18–25	−0.132***	−1.381***	−1.552***	−0.132***	−1.480***	−1.920***
	(0.045)	(0.223)	(0.221)	(0.040)	(0.213)	(0.281)
Age 41–65	0.103***	0.468***	1.061***	0.175***	0.928***	1.435***
	(0.031)	(0.143)	(0.162)	(0.031)	(0.138)	(0.232)
Age ≥ 66	0.099**	−0.981***	−0.345	0.132***	−0.163	−0.406
	(0.048)	(0.228)	(0.264)	(0.047)	(0.232)	(0.364)
Smoker	−0.266***	−0.490***	−1.658***	−0.177***	−0.660***	−1.887***
	(0.030)	(0.149)	(0.152)	(0.029)	(0.143)	(0.214)
Walk exercise	0.385***	−0.364***	0.452***	0.372***	−0.753***	0.527***
	(0.026)	(0.126)	(0.147)	(0.024)	(0.118)	(0.191)
Basic education	−0.203***	0.472**	−0.459**	−0.257***	1.545***	0.595**
	(0.040)	(0.202)	(0.189)	(0.033)	(0.178)	(0.235)
Some college	0.239***	−0.402***	0.201	0.216***	−0.602***	−0.266
	(0.033)	(0.153)	(0.172)	(0.030)	(0.145)	(0.228)
Bachelor	0.418***	−1.361***	0.060	0.488***	−2.235***	−1.676***
	(0.041)	(0.190)	(0.236)	(0.041)	(0.190)	(0.389)

Table 2
Continued

Variable	Men: Switching: Label use	Men: BMI (Label = 1)	Men: BMI (Label = 0)	Women: Switching: Label use	Women: BMI (Label = 1)	Women: BMI (Label = 0)
Graduate	0.457***	−1.754***	−0.619*	0.534***	−2.362***	−2.137***
	(0.051)	(0.227)	(0.323)	(0.060)	(0.246)	(0.652)
Outdoors		0.453**	0.376*		−0.801	0.788
		(0.196)	(0.207)		(0.575)	(0.665)
CPI food / 100		5.427	−1.689		−9.805**	−2.359
		(4.789)	(5.506)		(4.569)	(8.069)
Error std. dev. (σ_j)		4.694***	4.679***		5.644***	5.909***
		(0.041)	(0.057)		(0.037)	(0.088)
Concordance (θ, λ)		−3.828***	3.873***		−3.528***	3.235***
		(0.274)	(0.282)		(0.289)	(0.297)
Kendall's τ (τ_{j1})		−0.375***	0.378***		−0.352***	0.327***
		(0.021)	(0.022)		(0.023)	(0.025)
Log likelihood		−36668.394		−53812.186		
Correct prediction	64.40%			73.90%		
Efron's pseudo R^2	0.10			0.10		

Note: Asymptotic standard errors are in parentheses. Asterisks *** indicate significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 3
Average treatment effects: effect of food labels on BMI

Group	Men	Women
Full sample	−0.123**	−1.486***
	(0.191)	(0.311)
Black	0.534*	−0.528
	(0.305)	(0.365)
Other race	0.292	−0.232
	(0.376)	(0.456)
White	−0.250***	−1.762***
	(0.198)	(0.326)

Note: Asymptotic standard errors are in parentheses. Asterisks *** indicate significance at the 1% level, ** at the 5% level, and * at the 10% level.

of the NLEA labels was only effective in decreasing body weight among non-Hispanic white women. Our results show that females who read labels experience higher BMI reductions than their male counterparts. Nevertheless, more research is needed to shed some light into additional effects of nutritional labels. Variyam (2008) also reported positive impacts of NLEA labels on consumption habits. In particular, he showed that nutritional labeling use has a negative effect on the intake of total fat, saturated fat, cholesterol, and added sugar, and a positive effect on fiber, protein, calcium, iron Vitamin A and C, among others in food consumed at home. However, contradictory findings also exist in the literature, suggesting that the NLEA labels had no effect on BMI levels (Drichoutis et al., 2009). Teisl et al. (2001) also did not find that providing health-related information always leads consumers to switch from "unhealthy products" to more "healthy" alternatives. Specifically, they found that provision of nutrient information increased purchases of "healthy" products within four product categories but it also led to decreased purchases of "healthy" products within two product categories.

5. Concluding remarks and caveats

Concerns about the health of the U.S. population due to rising obesity have resulted in the legislation of the NLEA. So, can nutritional labeling help reduce obesity? The answer based on our results is generally yes. This finding is robust across gender although the effects are larger for females than for males. The effects of nutritional labels on BMI also differ across racial groups, with more notable effects among white males and females than those of other races. This finding has important public health implications considering that nutritional labels can be used as one of the instruments in combating obesity. Targeting by gender may also be useful in increasing the effectiveness of policy programs, since men are generally less active on reading labels and also have less pronounced label effects on BMI. Outreach campaigns related to nutritional label use can be most effective by promoting the use of nutritional labels among females, who are very often the primary grocery shoppers and food planners.

Nutritional labels are currently only mandatory for processed food products sold in the food at home market (i.e., supermarkets and grocery stores) in the U.S. The NLEA does not cover nutritional labeling in the food away from home market. Chou et al. (2004) revealed the important role that the expansion of food away from home played in increasing food availability and obesity in the U.S. Recent estimates suggest that Americans now spend close to half of every

food dollar on food away from home (USDA-ERS, 2008). Consequently, the availability of nutritional information in food away from home establishments like restaurants has been discussed by policy makers to help consumers make healthier food choices when eating out. Part of the health care reform bill that recently became law in the U.S. requires restaurants with 20 or more locations to list calorie content information for standard menu items on restaurant menus and menu boards. Hence, future studies should evaluate the influence of nutritional labeling in the food away from home market on dietary behavior and obesity.

Our findings highlight the potential impact of the current nutritional labeling policy, suggesting a differentiated impact across gender and racial groups. While we find that nutritional label use can reduce BMI, the magnitudes of the effects by gender suggest that nutritional labels may not by themselves reverse the tide of increasing obesity rates in the U.S. especially among males. However, they can be used as tools to educate Americans about the availability of nutritional information on the products they buy in supermarkets. They can also be used as complements to other weight-loss or obesity-reducing government-supported strategies or programs. Finkelstein et al. (2005) suggested that because obesity may result from poor information and addictive behavior, interventions will have to be multifaceted to ensure the best chance of success.

A few caveats pertain to the results presented here. First, the current findings are based on BMI as a measure of obesity. Virtually all social science research related to obesity uses BMI, which is usually calculated using self-reported values of weight and height. One limitation of BMI is that it does not distinguish fat from fat-free mass such as muscle and bone. Future studies might consider using additional measures of obesity such as total body fat, percentage of body fat, and waist circumference that have greater theoretical support in the medical literature (Cawley and Burkhauser, 2006). Second, this study uses a cross-sectional data set. An analysis based on longitudinal data at the individual level would be much richer and more informative for policy analysis, although such data are currently unavailable. Third, we use the 1998 NHIS survey, which might not adequately reflect recent effects of nutritional label use on obesity. For example, in 1998, consumers (especially those with basic nutrition knowledge) might have collected most of their nutrition information from labels but other information sources such as the Internet have since become increasingly relevant. These other information sources may reduce the effect of nutritional labels on recent health behavior. Fourth, as Variyam and Cawley (2006) suggest, the food industry might respond to mandatory labeling schemes by changes in food composition. As a result, the effects of nutritional labels on obesity will differ from those in the earlier periods of implementation of NLEA. Hence, future studies should utilize newer data sets to test the robustness of our findings. Finally, nutritional labels in the U.S. include information about nutrient content claims, nutrition facts panel, and health claims. Future studies, given data availability, might also repeat our analysis and investigate the effect of reading specific types of nutritional labels on obesity.

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Appendix: Switching regression model with Frank's copula

The copula approach to dependent models is motivated by a theorem due to Sklar (Nelsen, 2006, p. 18). Let H be a joint distribution function with margins F_1 and F_2. Then Sklar's theorem states that there exists a copula C such that for all y_1^*, y_2^* in the extended real line,

$$H(y_1^*,\ y_2^*) = C[F_1(y_1^*),\ F_2(y_2^*)]. \tag{A.1}$$

If F_1 and F_2 are continuous, then C is unique. Conversely, if C is a copula and F_1 and F_2 are distribution functions, then the function defined by (A.1) is a joint distribution function with margins F_1 and F_2. The copula approach has gained increasing popularity in recent times and has been applied in a variety of models including sample selection models (Smith, 2003, 2005). One class of copulas, the Archimedean copulas, proves particularly useful in econometric modeling with endogenous sample selection or regime switching (Smith, 2003).

To introduce the Archimedean class of copulas and to facilitate the development of the SRM, it is useful to consider a continuous and additive class of "generator function" $\varphi : [0, 1] \rightarrow [0, \infty]$, which is convex and decreasing ($\varphi'(t) = d\varphi(t)/dt < 0$, $\varphi''(t) = d^2\varphi(t)/dt^2 > 0$ for all $0 < t < 1$) and has terminal $\varphi(1) = 0$. In the bivariate case, φ generates the copula according to

$$\varphi(C(u, v)) = \varphi(u) + \varphi(v), \tag{A.2}$$

or, equivalently,

$$C(u, v) = \varphi^{-1}(\varphi(u) + \varphi(v)). \tag{A.3}$$

Let F_{12} be Archimedean copula with generator φ and F_{13} be Archimedean copula with generator η. Also, define additional notations $\eta'(t) = d\eta(t)/dt$, $F_1 = F_1(0)$, $F_2 = F_2(y_2)$, $F_3 = F_3(y_3)$, $f_2 = f_2(y_2)$, $f_3 = f_3(y_3)$, $C_\theta^{12} = \varphi^{-1}(\varphi(F_1) + \varphi(F_2))$, and $C_\lambda^{13} = \eta^{-1}(\eta(F_1) + \eta(F_3))$. Then, the likelihood function (6) simplifies to

$$L = \prod_{L=0} \frac{\eta'(F_3)}{\eta'(C_\lambda^{13})} f_3 \prod_{L=1} \left(1 - \frac{\varphi'(F_2)}{\varphi'(C_\theta^{12})}\right) f_2. \tag{A.4}$$

The ratio terms in Eq. (A.4) follows from the results that $\partial F_{12}(0,\ y_2)/\partial y_2 = (\varphi'(F_2)/\varphi'(C_\theta^{12}))f_2$ and $\partial F_{13}(0,\ y_3)/\partial y_3 = (\eta'(F_3)/\eta'(C_\lambda^{13}))f_3$ for Archimedean copulas F_{12} and F_{13} (Smith, 2003, p. 106, 110).

We use the Frank copula, a popular member of the Archimedean copula family, in this study. Below we present the copula, the generator and its derivative, and the dependence measure for the distribution function F_{12}. Presentation for F_{13} is similar. The Frank copula has the form (Nelsen, 2006; Smith, 2003)

$$C_\theta(u, v) = -\theta^{-1}\log(1 + (e^{-\theta u} - 1)(e^{-\theta v} - 1)/(e^{-\theta} - 1)),\quad -\infty < \theta < \infty, \tag{A.5}$$

created by the generator

$$\varphi(t) = -\log[(e^{-\theta t} - 1)/(e^{-\theta} - 1)], \tag{A.6}$$

which has derivative

$$\varphi'(t) = \theta[e^{-t\theta}/(e^{-t\theta} - 1)]. \tag{A.7}$$

The appropriate ratio term in the likelihood function (A.4) is therefore (Smith, 2003, p. 111)

$$\frac{\varphi'(F_2)}{\varphi'(C_\theta^{12})} = 1 - \frac{e^{\theta F_2}(e^{\theta F_1} - e^{\theta})}{e^{\theta(F_1+F_2)} + e^{\theta}(1 - e^{\theta F_1} - e^{\theta F_2})}. \tag{A.8}$$

In the above, θ is a measure of *concordance* (Nelsen, 2006, pp. 157–158) between the two random variables. A more useful measure of association between random variables y_1^* and y_2^*, parallel to the better known Pearson's product–moment correlation, is *Kendall's tau* which, for all Archimedean copulas, is defined as (Nelsen, 2006, p. 163)

$$\tau_{12} = 1 + 4\int_0^1 \frac{\varphi(t)}{\varphi'(t)}dt. \tag{A.9}$$

Frank's copula has a symmetric concordance parameter with an unrestricted coverage such that $-\infty \le \theta \le \infty$, which corresponds to $-1 \le \tau_{12} < 1$ and accommodates both positive and negative dependence. It is also "comprehensive" in that both Fréchet lower bound (corresponding to $\theta = -\infty$) and Fréchet upper bound (corresponding to $\theta = \infty$) are included in the range of permissible dependence, a desirable property of a distribution function and copula, which is the major reason it is chosen for this study.

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